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A nomogram for predicting delirium in the ICU among older patients with chronic obstructive pulmonary disease

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Abstract

Background Delirium is common among critically ill older patients with chronic obstructive pulmonary disease (COPD). This study aims to develop a nomogram model to predict the risk of ICU delirium in older patients with COPD.

Methods This study included 1,912 older COPD patients admitted to the ICU from the MIMIC-IV database. The patients were randomly divided into training and validation sets in a 7:3 ratio. LASSO regression, univariable and multivariable logistic regression were used to select the best predictive factors based on demographic, clinical, laboratory, and treatment data at ICU admission. A nomogram model was then constructed. The model's accuracy was evaluated using calibration curves. Its predictive performance and clinical utility were assessed using the area under the receiver operating characteristic curve (AUC), decision curve analysis (DCA), and clinical impact curves (CIC).

Results A total of 638 patients (33.4%) developed ICU delirium, with a median age of 76.00 (IQR: 71.00–83.00) years. Ten independent factors were identified for the nomogram model, including cerebrovascular disease (OR: 1.91; 95% CI, 1.38–2.64), Charlson Comorbidity Index (OR: 1.08; 95% CI, 1.02–1.13), Glasgow Coma Scale (OR: 0.82; 95% CI, 0.77–0.87), SOFA score (OR: 1.15; 95% CI, 1.07–1.22), heart rate (OR: 1.01; 95% CI, 1.01–1.02), body temperature (OR: 1.60; 95% CI, 1.14–2.24), blood urea nitrogen (OR: 1.01; 95% CI, 1.00-1.02), 24-hour urine output (OR: 1.02; 95% CI, 1.01–1.02), fentanyl (OR: 1.94; 95% CI, 1.47–2.55), and oxygen flow (OR: 1.04; 95% CI, 1.02–1.07). The model achieved an AUC of 0.86 (95% CI, 0.83–0.90) in the training set and 0.86 (95% CI, 0.84–0.88) in the validation set. The calibration curve showed good agreement between predicted and observed values ($P > 0.05$). DCA and CIC results indicated the model's strong predictive value and clinical applicability.

Conclusions This study developed an intuitive and simple nomogram model to predict the risk of ICU delirium in older patients with COPD. The model can help clinicians quickly identifying high-risk delirium patients upon ICU admission, thereby optimizing early intervention and treatment strategies.

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Keywords Chronic obstructive pulmonary disease, ICU delirium, MIMIC-IV database, Intensive care unit, Nomogram

Introduction

Delirium is an acute disorder of attention and cognitive function, characterized by fluctuating changes, and its specific physiological mechanisms are not yet fully understood [1]. In the intensive care unit (ICU), older patients aged 65 and above are at high risk for delirium [1, 2]. Studies show that up to 50% of hospitalized older patients experience delirium, with the incidence of ICU delirium ranging from 19–82% [2].

Chronic obstructive pulmonary disease (COPD) is a globally common chronic respiratory disease with high morbidity and mortality, particularly among the older people [3]. COPD not only manifests as a chronic respiratory condition but also involves systemic inflammatory responses. Patients often have hypoxemia and hypercapnia, and these pathological changes may increase the risk of delirium [4]. Studies indicate that the delirium incidence in COPD patients receiving mechanical ventilation can be as high as 21.94% [5]. Delirium not only prolongs the duration of mechanical ventilation but also increases the risk of short-term or long-term cognitive impairment, complications, and mortality [1, 6]. Delirium patients often exhibit poor cooperation and are at risk of events like accidental extubation, further increasing the clinical nursing burden. Research has shown that nursing pressure in COPD patients with delirium is even higher than that in patients in intensive respiratory care units [7]. Currently, the treatment strategies for delirium in critically ill COPD patients are limited, and early detection and prevention remain the most effective methods [1, 8].

Risk prediction models are valuable tools for assessing the risk of ICU delirium. Several models have been developed for ICU delirium risk prediction, each with its own strengths and limitations. The PRE-DELIRIC (PREdiction of DELIRium in ICu patients) model, the E-PRE-DELIRIC (Early PREdiction model for DELIRium in ICu patients) model, and the Lanzhou model are validated and commonly used for ICU delirium prediction [9–11]. However, the Lanzhou model heavily relies on patients' medical history, limiting its widespread application [12]. The PRE-DELIRIC model has the highest prediction accuracy but is less convenient than the E-PRE-DELIRIC model [13]. These models are primarily designed for general ICU patients, making them more universal, but their predictive effectiveness in specific populations or specialty ICUs is limited [14–16].

Despite the high incidence and impact of ICU delirium in older patients with COPD, no targeted prediction model is currently available for this specific population. Therefore, this study aims to identify factors associated with ICU delirium in older COPD patients and develop an intuitive nomogram model for risk prediction.

Materials and methods

Data sources and processing

This study was conducted in accordance with the principles of the Declaration of Helsinki and was approved by the Institutional Review Boards of the Massachusetts Institute of Technology and Beth Israel Deaconess Medical Center. As a retrospective study, all patient data from the Medical Information Mart for Intensive Care (MIMIC-IV) database were de-identified in compliance with the Health Insurance Portability and Accountability Act (HIPAA), and therefore, patient consent was not required. The MIMIC-IV database is an open-access public resource containing a large volume of high-quality, anonymized patient data from the ICU of Beth Israel Medical Center in Boston [17]. One of our team members completed the relevant courses of the Collaborative Institutional Training Initiative (CITI) and was granted database access (Certification Number: 62506785).

This study used version 2.2 of the MIMIC-IV database, and data were extracted using Structured Query Language (SQL) via Navicat Premium software (version 16.3.8). Older ICU patients with COPD from the MIMIC-IV version 2.2 database who met the following inclusion and exclusion criteria were selected as study participants. **Inclusion criteria: F**irst-time ICU admission with a hospital stay exceeding 24 h; a confirmed diagnosis of COPD; age ≥ 65 years; and availability of complete delirium assessment records. **Exclusion criteria**: Severe mental illnesses (e.g., schizophrenia, depression); suicidal tendencies; neurodegenerative diseases (e.g., dementia, Parkinson's disease); hypoxic or traumatic brain injury; hepatic encephalopathy; deafness or blindness. The study design flow is illustrated in Figure S1.

Potential predictors

Potential predictive variables included: (1) Demographic characteristics include age, gender, weight, race, marital status, insurance; (2) Pre-existing comorbidity at admission: myocardial infarction, congestive heart failure, peripheral vascular disease, cerebrovascular disease, rheumatic disease, liver disease, diabetes, renal disease, cancer. The Charlson Comorbidity Index (CCI) was used to assess comorbidity burden; (3) Clinical scores obtained within 24 h of admission: glasgow coma scale (GCS), sequential organ failure assessment (SOFA); (4) Vital signs within 24 h of admission: heart rate, mean blood pressure (MBP), respiratory rate, systolic blood pressure (SBP), temperature, oxygen saturation (SpO_2);

(5) Laboratory characteristics within 24 h of admission: hematocrit, hemoglobin (Hb), red blood cells (RBC), white blood cells (WBC), bicarbonate, calcium (Ca), chloride (Cl), sodium (Na), potassium (K), serum creatinine, blood urea nitrogen (BUN), blood glucose, platelet, prothrombin time (PT), international normalized ratio (INR), blood pH, arterial partial pressure of oxygen (PO_2), arterial partial pressure of carbon dioxide (PCO_2), and 24-hour urine output; (6) Therapeutic factors within 7 days of admission: phenylephrine, acetaminophen, fentanyl, midazolam, propofol, epinephrine, renal replacement therapy (RRT), mechanical ventilation, and oxygen flow. For patients who developed delirium, only data prior to the onset of delirium were used in the analysis.

Outcomes

This study used the CAM-ICU to assess delirium occurrence within 7 days of ICU admission. The CAM-ICU scale is a guideline-recommended bedside assessment tool that plays an important role in early delirium detection [18]. A positive CAM-ICU diagnosis is based on the presence of acute changes or fluctuations in mental status (Feature 1) and inattention (Feature 2), along with either disorganized thinking (Feature 3) or altered level of consciousness (Feature 4). If any of these conditions are met, the patient is diagnosed with delirium [19].

Statistical analysis

For continuous variables with non-normal distribution, the median (interquartile range, IQR) is presented, and the Mann-Whitney U test is used for intergroup comparisons. Categorical variables are expressed as frequencies (percentages), with the Chi-square test or Fisher's exact test used for group comparisons. A total of 1,912 patients were included in this study, divided randomly into training ($n = 1,337$) and validation ($n = 575$) sets at a 7:3 ratio.

All variables included in the study had a missing rate below 30%, with detailed patterns of missingness presented in Table S1. Missing data were addressed using multiple imputation by chained equations (MICE) via the "mice" package in R, with the random forest method. All candidate predictors were included in the imputation models to preserve the multivariable structure. To reduce multicollinearity and overfitting, Least Absolute Shrinkage and Selection Operator (LASSO) regression model was applied to select predictive variables from 52 potential predictors in the training set. The optimal tuning parameter (λ) was determined using 10-fold cross-validation to ensure robust internal validation [20]. LASSO regression was performed independently in each imputed dataset, and based on the frequency approach [21], the predictors that identifing by at least a half of the imputed datasets was selected for model development (Table S2). Subsequently, the selected variables were then included in univariable logistic regression analysis. Significant variables were further analyzed using multivariable logistic regression. The variables that remained statistically significant in the multivariable analysis were used to construct the nomogram model.

The predictive performance of the model was evaluated using the receiver operating characteristic (ROC) curve, with the area under the curve (AUC) as the primary performance metric. The calibration of the model was assessed using the Hosmer-Lemeshow test and calibration curve. Decision curve analysis (DCA) and clinical impact curve (CIC) were also used to evaluate the clinical utility and net benefit of the model.

To assess the potential impact of missing data, a sensitivity analysis was performed using the complete-case dataset. Additionally, to clarify the impact of delirium on the survival of these patients, Kaplan-Meier (KM) survival curves were plotted and analyzed using the log-rank test and univariable and multivariable Cox proportional hazards models.

All statistical analyses were conducted using R 4.3.2 software, and a two-tailed P-value of less than 0.05 was considered statistically significant.

Results

Participant characteristics

A total of 1,912 older patients with COPD who were admitted to the ICU for the first time were included in this study. Table 1 shows the baseline characteristics of the participants. Among these, 638 patients (33.4%) developed delirium within the first week of admission. The median age of the patients was 76.00 years [IQR: 71.00–83.00], with 1,005 patients (52.6%) being male and 1,373 patients (71.8%) being white. Compared to the non-delirium group, the proportion of white patients was lower in the delirium group. Additionally, delirium patients showed significant differences in the CCI, GCS, SOFA score, and various baseline characteristics ($P < 0.05$). Delirious patients had significantly longer hospital stays ($P < 0.001$) and higher in-hospital mortality rates ($P < 0.001$). Survival analysis (Figure S2) and Cox regression (Table S3) further confirmed that delirium is a significant risk factor for mortality (HR: 1.91, 95% CI: 1.66–2.20, $P < 0.001$). The baseline characteristics of the complete-case dataset were generally similar to those of the imputed dataset (Table S4). There were no significant differences in baseline characteristics (all $P > 0.05$) between the training and validation groups (Table S5).

Selection of predictive variables

After LASSO regression analysis, 14 delirium predictors were selected from the 52 potential variables, including cerebrovascular disease, CCI, GCS, SOFA, heart rate, respiratory rate, temperature, BUN, RBC, 24-hour urine

Table 1 Baseline characteristics of older participants with COPD according to the development or not of ICU delirium

Variables	Total (*N* = 1912)	Non-delirium (*N* = 1274)	Delirium (*N* = 638)	*P*-value
Demographics				
Age, M[IQR]	76.00 [71.00, 83.00]	76.00 [71.00, 83.00]	76.00 [71.00, 83.00]	0.845
Gender, n (%)				0.117
Male	907(47.4)	621(48.7)	286(44.8)	
Female	1005 (52.6)	653 (51.3)	352 (55.2)	
Weight (kg), M[IQR]	78.70 [65.00, 93.82]	78.50 [65.00, 92.42]	79.00 [65.00, 97.77]	0.106
Race, n (%)				0.020
White	1373 (71.8)	935 (73.4)	438 (68.7)	
Black	146 (7.6)	100 (7.8)	46 (7.2)	
Asian	34 (1.8)	22 (1.7)	12 (1.9)	
Hispanic/Latino	45 (2.4)	33 (2.6)	12 (1.9)	
Other	314 (16.4)	184 (14.4)	130 (20.4)	
Marital status, n (%)				0.976
Married	916 (47.9)	609 (47.8)	307 (48.1)	
Divorced	189 (9.9)	125 (9.8)	64 (10.0)	
Single	385 (20.1)	255 (20.0)	130 (20.4)	
Widowed	422 (22.1)	285 (22.4)	137 (21.5)	
Insurance, n (%)				0.211
Medicare	1263 (66.1)	826 (64.8)	437 (68.5)	
Medicaid	25 (1.3)	19 (1.5)	6 (0.9)	
Other	624 (32.6)	429 (33.7)	195 (30.6)	
Admission				
Comorbidities				
CCI, M[IQR]	7.00 [5.00, 9.00]	6.00 [5.00, 8.00]	7.00 [5.00, 9.00]	< 0.001
Myocardial infarction, n (%)	510 (26.7)	348 (27.3)	162 (25.4)	0.370
Congestive heart failure, n (%)	895 (46.8)	585 (45.9)	310 (48.6)	0.270
Peripheral vascular disease, n (%)	412 (21.6)	284 (22.3)	128 (20.1)	0.264
Cerebrovascular disease, n (%)	279 (14.6)	162 (12.7)	117 (18.3)	0.001
Rheumatic disease, n (%)	108 (5.7)	76 (6.0)	32 (5.0)	0.396
Diabetes, n (%)	715 (37.4)	475 (37.3)	240 (37.6)	0.887
Liver disease, n (%)	117 (6.1)	67 (5.3)	50 (7.8)	0.034
Renal disease, n (%)	570 (29.8)	339 (26.6)	231 (36.2)	< 0.001
Cancer, n (%)	330 (17.3)	207 (16.3)	123 (19.3)	0.098
Scoring systems, **M[IQR]**				
GCS	15.00 [14.00, 15.00]	15.00 [14.00, 15.00]	14.00 [13.00, 15.00]	< 0.001
SOFA	2.92 [1.54, 4.76]	2.34 [1.08, 3.89]	4.24 [2.79, 6.15]	< 0.001
Vital signs, **M[IQR]**				
Heart rate mean (bpm)	82.18 [72.88, 94.16]	81.07 [72.63, 91.99]	84.59 [74.44, 98.60]	< 0.001
MBP mean (mmHg)	75.74 [70.21, 83.10]	76.24 [70.44, 83.41]	75.04 [69.92, 82.54]	0.037
SBP (mmHg)	116.14 [106.78, 127.95]	117.19 [107.55, 128.38]	113.74 [105.31, 126.68]	< 0.001
Respiratory rate mean (rpm)	19.37 [17.18, 21.88]	19.19 [17.11, 21.58]	19.62 [17.46, 22.43]	0.001
Temperature mean (℃)	36.79 [36.64, 36.98]	36.76 [36.63, 36.92]	36.86 [36.65, 37.11]	< 0.001
SpO_2 mean (%)	96.28 [94.74, 97.65]	96.16 [94.62, 97.42]	96.57 [94.96, 98.05]	< 0.001
Laboratory test, **M[IQR]**				
Hematocrit (%)	32.30 [27.90, 37.00]	32.48 [27.96, 37.20]	31.95 [27.56, 36.25]	0.036
Hemoglobin (g/dL)	10.35 [8.90, 11.95]	10.45 [9.05, 12.05]	10.10 [8.71, 11.69]	0.001
RBC (*10^9/L)	3.35 [2.96, 3.84]	3.45 [3.01, 3.94]	3.22 [2.84, 3.63]	< 0.001
WBC (*10^9/L)	11.15 [8.25, 14.96]	10.70 [7.90, 14.50]	12.25 [9.06, 15.67]	< 0.001
Bicarbonate (mmol/L)	23.50 [21.00, 26.00]	24.00 [21.50, 26.00]	23.00 [20.12, 25.50]	< 0.001
Calcium (mg/dL)	8.40 [7.95, 8.85]	8.40 [8.00, 8.90]	8.30 [7.85, 8.80]	0.004
Chloride (mEq/l)	102.50 [99.00, 106.00]	102.50 [99.00, 105.50]	102.50 [98.50, 106.00]	0.649
Sodium (mEq/l)	138.00 [136.00, 141.00]	138.00 [136.00, 140.50]	138.50 [135.50, 141.50]	0.096
Serum creatinine (mg/dL)	1.05 [0.80, 1.55]	1.00 [0.75, 1.40]	1.20 [0.80, 1.90]	< 0.001

Table 1 (continued)

Variables	Total (*N* = 1912)	Non-delirium (*N* = 1274)	Delirium (*N* = 638)	*P*-value
Glucose (mg/dL)	131.00 [109.00, 164.00]	128.75 [108.00, 158.50]	138.75 [114.00, 177.88]	< 0.001
Potassium (mEq/l)	4.30 [3.95, 4.70]	4.30 [3.95, 4.60]	4.40 [4.00, 4.85]	< 0.001
Platelet (*10^9/L)	188.00 [142.00, 246.62]	189.50 [147.00, 247.25]	183.50 [134.62, 246.50]	0.103
INR	1.20 [1.10, 1.40]	1.20 [1.10, 1.35]	1.25 [1.10, 1.45]	< 0.001
PT (s)	13.10 [11.65, 15.20]	12.97 [11.51, 14.85]	13.43 [11.80, 15.89]	< 0.001
pH	7.37 [7.33, 7.41]	7.37 [7.34, 7.41]	7.37 [7.33, 7.40]	0.009
PO_2 (mmHg)	91.25 [60.00, 145.19]	93.00 [57.59, 165.90]	90.91 [64.11, 129.78]	0.309
PCO_2 (mmHg)	44.00 [39.00, 50.16]	43.72 [39.28, 49.70]	44.41 [39.00, 50.98]	0.169
BUN (mg/dL)	22.68 [16.28, 34.87]	21.00 [15.55, 31.14]	27.25 [18.46, 43.23]	< 0.001
24-hour urine output (ml)	1290.48 [778.25, 1893.45]	1184.76 [752.93, 1763.69]	1517.24 [873.96, 2259.82]	< 0.001
Therapeutic factor, n (%)				
Phenylephrine	378 (19.8)	202 (15.9)	176 (27.6)	< 0.001
Acetaminophen	327 (17.1)	193 (15.1)	134 (21.0)	0.002
Fentanyl	319 (16.7)	63 (4.9)	256 (40.1)	< 0.001
Midazolam	91 (4.8)	26 (2.0)	65 (10.2)	< 0.001
Propofol	618 (32.3)	274 (21.5)	344 (53.9)	< 0.001
Epinephrine	101 (5.3)	54 (4.2)	47 (7.4)	0.006
RRT	130 (6.8)	56 (4.4)	74 (11.6)	< 0.001
Mechanical ventilation				< 0.001
No	1175 (61.5)	945 (74.2)	230 (36.1)	
IMV	695 (36.3)	296 (23.2)	399 (62.5)	
NPPV	42 (2.2)	33 (2.6)	9 (1.4)	
O_2 flow (L/min), M [IQR]	3.55 [2.33, 5.93]	3.17 [2.11, 4.83]	4.81 [3.00, 8.87]	< 0.001
Outcomes				
Length of ICU (day), M [IQR]	2.15 [1.27, 4.21]	1.73 [1.10, 2.90]	4.38 [2.34, 8.32]	< 0.001
Length of hospital (day), M[IQR]	7.87 [4.95, 13.63]	6.76 [4.55, 10.74]	11.88 [6.92, 20.43]	< 0.001
Hospital mortality, n (%)	160 (8.4)	45 (3.5)	115 (18.0)	< 0.001

M[IQR]: median [interquartile range]; CCI: Charlson Comorbidity Index; GCS: Glasgow Coma Scale; SOFA: sequential organ failure assessment; bpm: beats per minute; IRBC: red blood cell; WBC: white blood cell; INR: international normalized ratio; PT: prothrombin time; MBP: mean blood pressure; SBP: systolic blood pressure; SpO_2: oxygen saturation; PO_2: arterial partial pressure of oxygen; PCO_2: arterial partial pressure of carbon dioxide; pH: potential of hydrogen; BUN: blood urea nitrogen; RRT: renal replacement therapy; IMV: invasive mechanical ventilation; NPPV: noninvasive positive pressure ventilation

output, fentanyl, propofol, mechanical ventilation, and oxygen flow (Fig. 1). These 14 variables were included in univariable and multivariable logistic regression analyses, ultimately identifying 10 independent predictors of delirium in older patients wiht COPD, which were used for the construction of the prediction model (Table 2). The variables are as follows: cerebrovascular disease (OR 1.91; 95% CI, 1.38–2.64; $P < 0.001$), CCI (OR 1.08; 95% CI, 1.02–1.13; $P = 0.006$), GCS (OR 0.82; 95% CI, 0.77–0.87; $P < 0.001$), SOFA (OR 1.15; 95% CI, 1.07–1.22; $P < 0.001$), heart rate (OR 1.01; 95% CI, 1.01–1.02; $P = 0.006$), temperature (OR 1.60; 95% CI, 1.14–2.24; $P = 0.002$), BUN (OR 1.01; 95% CI, 1.00-1.02; $P = 0.034$), 24-hour urine output (OR 1.02; 95% CI, 1.01–1.02; $P < 0.001$), fentanyl (OR 1.94; 95% CI, 1.47–2.55; $P < 0.001$), and oxygen flow (OR 1.04; 95% CI, 1.02–1.07; $P < 0.001$). Sensitivity analysis demonstrated that the results of LASSO selection (Table S2) and regression analyses based on the complete-case dataset were generally consistent with those derived from the imputed datasets (Table S6).

Predictive model development

A predictive model was developed based on variables with a *P*-value < 0.05 in the multivariable logistic regression analysis and visualized using a nomogram (Fig. 2). The nomogram includes 10 independent predictive factors. The score for each factor can be determined by drawing a vertical line from the dot axis, and the total score is calculated by summing all factor scores. The total score can then be used to estimate the risk of delirium. This approach enables individualized risk assessment for delirium in older patients with COPD admitted to the ICU.

Validation of the predictive model

Fig. 3(A) and Fig. 3(B) illustrate the comparable accuracy of the predictive model in both the training and validation datasets. The AUC was 0.86 (95% CI: 0.83–0.90) in the training set and 0.86 (95% CI: 0.84–0.88) in the validation set. These results indicate that the nomogram has strong discriminatory power, effectively distinguishing between patients with and without delirium.

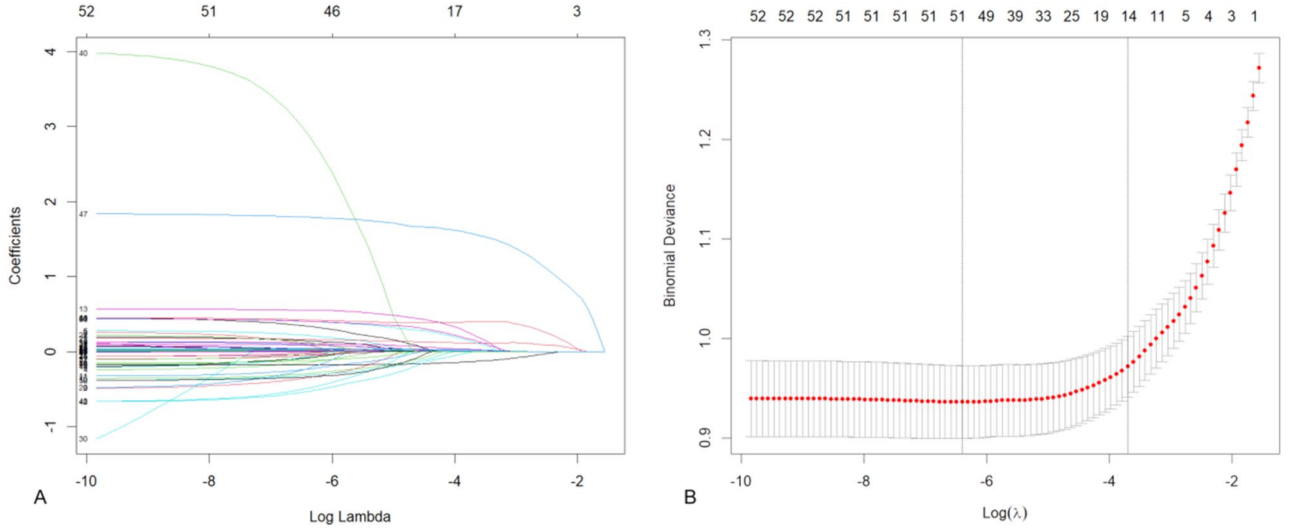

Fig. 1 Variable Selection Plot Based on LASSO Regression. (**A**): Coefficient Distribution Plot; (**B**): 10-Fold Cross-Validation Statistics Plot in LASSO Regression. The regularization parameter (lambda) for LASSO regression was determined using the minimum criterion (lambda.min, left dashed line) and the 1-SE criterion (lambda.1se, right dashed line). In this study, the 1-SE criterion was selected, resulting in 14 non-zero coefficients for variable selection

Table 2 Predictors of ICU delirium: univariable and multivariable logistic regression analyses of variables selected by LASSO

Variables	Univariable logistic analysis		Multivariable logistic analysis	
	OR (95% CI)	*P*-value	OR (95% CI)	*P*-value
Cerebrovascular disease	1.94 (1.40, 2.68)	< 0.001	1.91 (1.38, 2.64)	< 0.001
CCI	1.07 (1.02, 1.13)	0.009	1.08 (1.02, 1.13)	0.006
GCS	0.82 (0.77, 0.87)	< 0.001	0.82 (0.77, 0.87)	< 0.001
SOFA	1.12 (1.05, 1.20)	0.001	1.15 (1.07, 1.22)	< 0.001
Heart rate (bpm)	1.01 (1.00, 1.02)	0.011	1.01 (1.01, 1.02)	0.006
Temperature (℃)	1.50 (1.07, 2.16)	0.020	1.60 (1.14, 2.24)	0.002
BUN (mg/dL)	1.01 (1.00, 1.02)	0.004	1.01 (1.00, 1.02)	0.034
24-hour Urine output (100mL)	1.01 (1.00, 1.03)	0.045	1.02 (1.01, 1.02)	< 0.001
Fentanyl	6.43 (4.48, 9.32)	< 0.001	1.94 (1.47, 2.55)	< 0.001
O_2 flow (L/min)	1.04 (1.02, 1.06)	< 0.001	1.04 (1.02, 1.07)	< 0.001
Propofol	1.52 (0.98, 2.32)	0.057	-	-
Mechanical ventilation				
IMV	1.46 (0.93, 2.29)	0.101	-	-
NPPV	1.02 (0.44, 2.14)	0.987	-	-
RBC (*10^9/L)	0.82 (0.68, 1.00)	0.055	-	-

Variables not included in the final multivariable model are marked as "-"; OR: Odds Ratio; 95% CI: 95% Confidence Interval; CCI: Charlson Comorbidity Index; GCS: Glasgow Coma Scale; SOFA: Sequential Organ Failure Assessment; BUN: Blood Urea Nitrogen; bpm: beats per minute; IMV: invasive mechanical ventilation; NPPV: noninvasive positive pressure ventilation; RBC: red blood cell

The calibration curves (Fig. 4) demonstrate good agreement between the predicted and observed probabilities of delirium, suggesting high reliability of the model for delirium risk prediction. The Hosmer-Lemeshow goodness-of-fit test showed excellent calibration in both the training set (χ^2 = 11.32, df = 8, P = 0.184) and the validation set (χ^2 = 11.60, df = 8, P = 0.170), further supporting the model's accuracy.

Clinical utility was evaluated using DCA and CIC. DCA (Fig. 5A and B) indicated substantial net benefit within a risk threshold range of 0.1 to 0.8, underscoring the model's good clinical applicability. CIC (Fig. 5C and D) further validated the model's predictive capability, confirming its feasibility and reliability in real-world applications.

Discussion

This study found that the incidence of delirium among older patients with COPD in the ICU was as high as 33%, significantly higher than that observed in general geriatric wards [2]. Furthermore, the study demonstrated that the occurrence of delirium was closely associated with prolonged hospitalization and shortened survival, consistent with previous findings [22]. Delirium is a highly

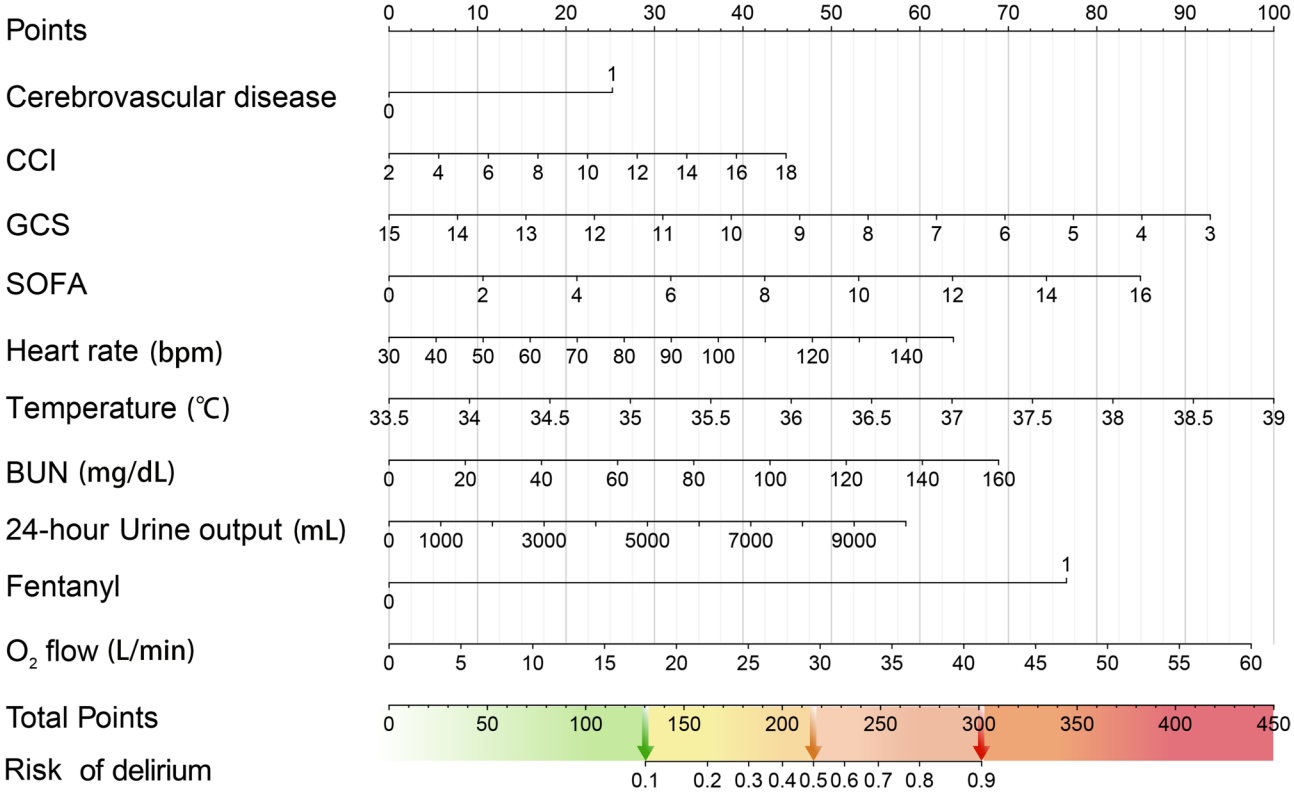

Fig. 2 Nomogram Prediction Model for Delirium Occurrence in Older Patients with COPD in the ICU. CCI: Charlson Comorbidity Index; GCS: Glasgow Coma Scale; SOFA: Sequential Organ Failure Assessment; BUN: Blood Urea Nitrogen; In accordance with standard clinical documentation practices, the 24-hour urine output is displayed in mL, which is the conventional unit of measurement

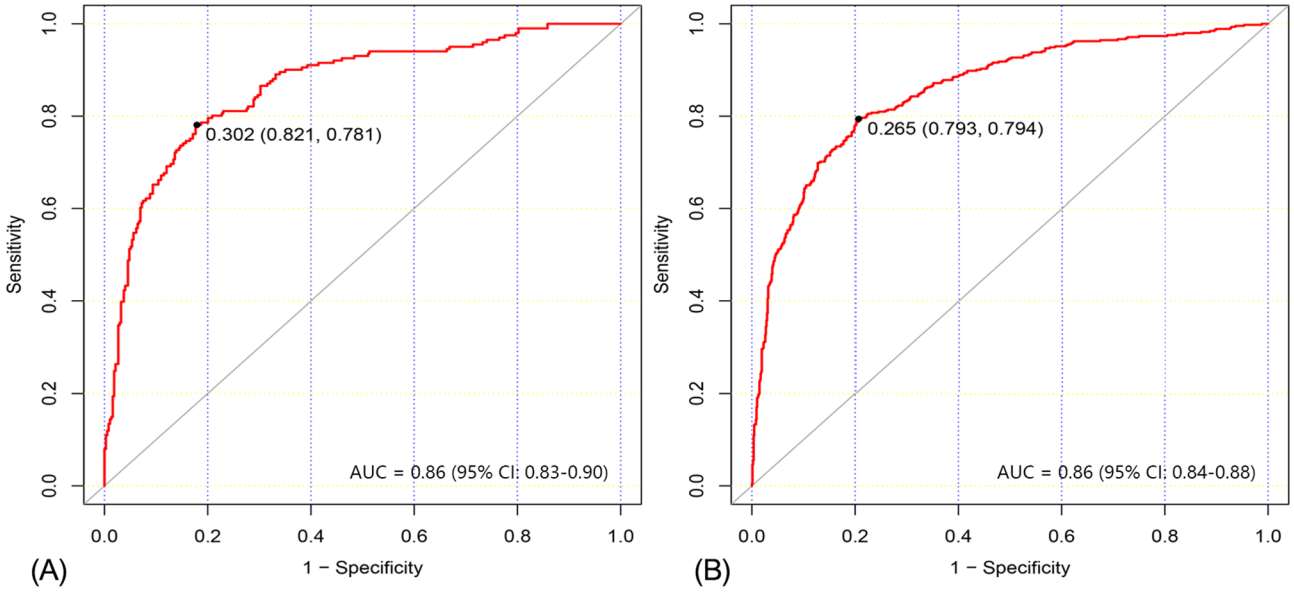

Fig. 3 ROC curves of the Nomogram prediction model in the validation cohort (**A**) and the training cohort (**B**). 95% CI: 95% confidence interval; AUC: area under the curve

heterogeneous condition influenced by various factors, with triggers differing across patient populations [23, 24]. Therefore, identifying predictors of ICU delirium in older patients with COPD and developing a prediction model are crucial for early identification of high-risk individuals, prevention of delirium, and improved outcomes.

This study is the first to develop and internally validate a nomogram-based prediction model to estimate the

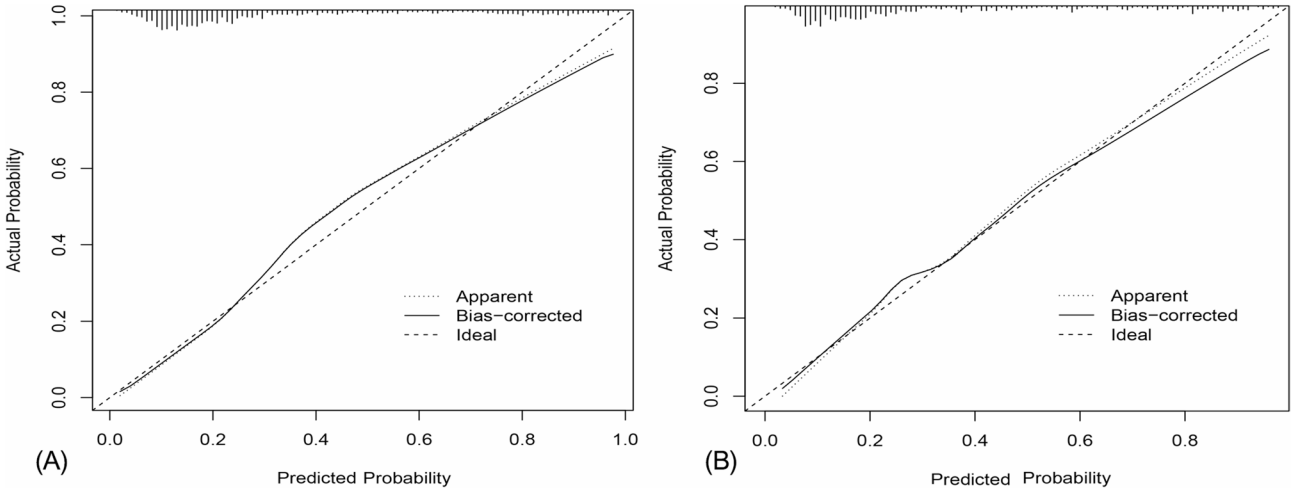

Fig. 4 Calibration curve plots of the Nomogram prediction model in the validation group (**A**) and the training group (**B**)

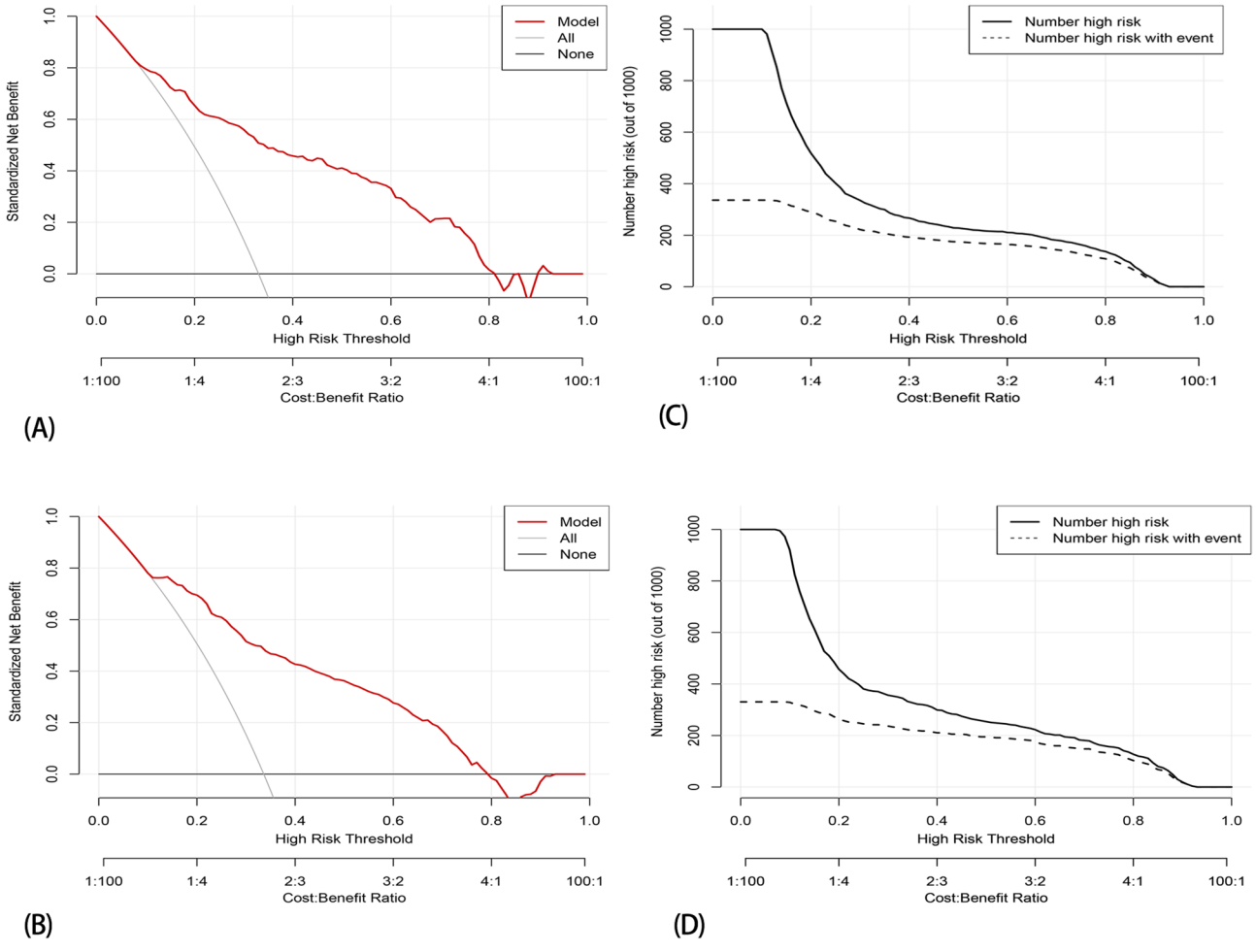

Fig. 5 DCA and CIC of the Nomogram prediction model in the validation group (**A, C**) and the training group (**B, D**)

risk of ICU delirium in older patients with COPD. The results showed that the model had good discriminatory ability and high clinical utility. The nomogram integrates 10 easily accessible available predictors at ICU admission and visually presents the prediction results of a complex model, making it intuitive and applicable. Compared to traditional prediction models, the nomogram offers better user-friendliness and reliability, providing strong

support for clinical decision-making [25]. The total score derived from the nomogram can evaluate a patient's delirium risk, where higher scores indicate higher risks. For instance, a total score below 130 corresponds to a delirium risk of less than 10%, whereas a score exceeding 215 indicates a risk above 50%. However, this study did not define specific thresholds for risk levels. On one hand, clinical conditions are highly variable, and a single risk threshold may not fully capture individual differences. On the other hand, the nomogram aims to provide individualized risk probabilities, enabling clinicians to apply it flexibly based on the patient's specific circumstances. For high-risk patients, the nomogram highlights key risk factors facilitating targeted interventions to reduce the incidence of delirium. For patients at low to moderate risk, healthcare providers can allocate resources efficiently based on the estimated risk probabilities, optimizing care delivery.

The predictive model includes cerebrovascular disease, CCI, GCS, SOFA, heart rate, BUN, temperature, 24-hour urine output, fentanyl, and oxygen flow. While some factors have been included in previous ICU delirium prediction models [11, 26–31], several variables were identified for the first time as being closely associated with ICU delirium in older patients with COPD. Specifically, this study found that fentanyl use significantly increased the risk of delirium, with an odds ratio of 1.94 (95% CI: 1.47–2.55), higher than the findings by Aoki et al. [32]. This suggests that the impact of fentanyl use may be more pronounced COPD patients than in those undergoing mechanical ventilation in ICU. Exploring alternative analgesic options or optimizing fentanyl use strategies may help mitigate delirium risk. Additionally, temperature fluctuations, particularly hyperthermia, were identified as significant risk factors [33, 34]. Hyperthermia may exacerbate brain injury and trigger delirium by enhancing neurotransmitter release, increasing oxidative stress, and compromising the integrity of the blood-brain barrier [35, 36]. Similarly, excessive oxygen flow may lead to CO_2 retention and acidosis in COPD patients, further contributing to delirium. It is recommended to maintain appropriate oxygen saturation and regularly monitor arterial blood gas levels in COPD patients [37]. Notably, while urinary retention has been previously recognized as a potential risk factor for delirium, this study found that excessive urine output also significantly increased delirium risk, consistent with the findings of Sheng et al. [38, 39]. Polyuria may reflect fluid overload, potentially leading to complications such as pulmonary edema, heart failure, and cognitive dysfunction. This highlights the importance of meticulous fluid management to mitigate associated risks.

Despite these significant findings, this study has several limitations. First, as a retrospective single-center study based on the MIMIC-IV database, only internal validation was performed. Future studies should conduct external validation and prospective multicenter studies to enhance the model's accuracy and robustness. Second, although this study included COPD patients, COPD may not have been the primary diagnosis for all patients. Despite accounting for common comorbidities, the complex health conditions of ICU patients may introduce bias. To minimize the confounding effect of the bidirectional relationship between cognitive impairment and delirium on the model's applicability to COPD patients [40, 41], we excluded patients with conditions potentially associated with cognitive impairment. While this enhanced the model's relevance to the target population, it also limited its generalizability. Additionally, manual calculations required for the nomogram may not be efficient in busy clinical settings. Developing complementary digital tools in the future could enhance its practicality and ease of use in clinical practice.

Conclusions

We developed a nomogram prediction model for ICU delirium in older patients with COPD, which demonstrated good discriminative ability and potential clinical utility based on internal validation. This model may assist clinical staff in intuitively assessing delirium risk and facilitating timely interventions and optimized treatment strategies. However, prospective validation in larger and more diverse populations is warranted to further assess its robustness and generalizability.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12877-025-06049-7.

Supplementary Material 1

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Author contributions

Chunchun Yu: Methodology, Software, Formal analysis, Data collection, Writing - original draft, Writing - review & edition. Tianye Li: Writing - review & edition. Mengying Xu: Data collection. Hao Xu：Data Curation. Xiong Lei: Conceptualization, Data Curation. Zhixiao Xu: Data collection, Data Curation. Jianming Hu：Data Curation, Writing - review & edition. Xiuyun Zheng: Writing - review & edition, Supervision. Chengshui Chen: Conceptualization, Supervision. Hongjun Zhao: Writing - Review & Edition, Supervision. All the authors of this article have contributed important intellectual content.

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Data availability
The datasets generated during and/or analyzed during the current study are available in [https://physionet.org/content/mimic-iv-ed/2.2/].

Declarations

Ethics approval and consent to participate
All procedures performed in the present study were in accordance with the principles outlined in the 1964 Helsinki Declaration and its later amendments. This study was exempted from obtaining informed consent. Because the MIMIC IV database has received ethical approval from the Massachusetts Institute of Technology (Cambridge, MA) and Beth Israel Deaconess Medical Center (Boston, MA) its data is publicly available and all patient data are de-identified. In addition, this study was registered and passed the Ethics Committee of the First Affiliated Hospital of Wenzhou Medical University and our clinical trial number was 2016131.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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